Interpretable Network Traffic Classification by **Integrating Human Expertise with Machine Learning**

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Fraunhofer IGD Darmstadt Information Visualization and Visual Analytics (IVA) Supervised by Prof. Dr.-Ing. Jörn Kohlhammer

Motivation

- Current situation with ML models
 - Learn hidden relationships in data
 - Excellent performance classification and anomaly detection
- Our goals in fusion with VA:
 - Classification alone is not enough (lacking trust, validation, and understanding)
 - Leverage machine learning for valuable insights
 - Enhance ML systems with domain knowledge



Our case study in cybersecurity

Data

• Network data provided in the form of PCAP files



Network data is often compared to an onion with a header for each layer, followed by the payload.

Our case study in cybersecurity

Data

- Network data provided in the form of PCAP files
- User
 - Administrators
 - Cybersecurity professionals
 - Malware analysts
- Tasks
 - Develop and enforce security policies and procedures
 - Optimize Quality of Service (QoS)
 - Manage network resources

Progress on our framework



Visual Analytics for Network Packet Captures

NetCapVis: Web-based Progressive Visual Analytics for Network Packet Captures

Alex Ulmer*

Jörn Kohlhammer[‡]

- Visual analytics system for analyzing PCAP data
- Parsing of PCAP files
- Interlinked visualization of
- network statistics, including:
 - Network graph
 - Timeline view
 - Bar charts
 - Listing of IP addresses and protocols

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ML Integration into the Framework



ML Integration into the Framework

- Researched and compared different ML approaches
 - 1D-CNN model achieved the best performance (confirmed by the field of network research)
- Applied 1D-CNN and evaluated
 - Experimenting with hidden layer depth and width
 - Adjusted convolutional filter sizes
- Created a custom dataset
 - Includes novel and modern application classes (youtube, facebook ...)

- Network packets resemble images, they are one-dimensional, and neighboring bits are frequently related.
- XAI methods from image processing are suitable
 - Class Activation Maps





B. Zhou, A. Khosla, A. Lapedriza, A. Oliva and A. Torralba, "Learning Deep Features for Discriminative Localization," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

CAM Calculation:

- The predicted class score is mapped back to the previous convolutional layer to create the CAMs. The resulting CAM is a sum of all convolutional feature maps of the last convolutional layer multiplied by the weights of output layer.
- Computationally cheap
- calculated directly on the resulting trained model





impact for the classified application class
Legend
Low
High

- Overview of all packets with predicted class
- Packets can be viewed in raw format or as a folded tree structure showing all segments
- Investigation of the most impactful bytes in a PCAP file for a predicted application class.

Visualization Of Class Activation Maps To Explain AI Classification Of Network Packet Captures

lgor	Cherepan	ov*	Alex Uln	ner†	Jonath	an Gera	aldi Joev	vono ‡	Jörn Kohl	hammer [§]
			Tec	hnische L	Fraunhof Jniversität		t, German	у		
Time	Predicted Class 4	Probability	Src. IP	Src. Port	Duct. IP	Dest. Pari	Protocol	Payload in Dytes	In / Out / Internal	Info
		0.99946076								
2.5.2022 09:21:05	Zoom	0.99946076		48092		9303		585.0	Incoming	443-+63061(ACK) Win-646
2.5.2022 09:21:05	zosm (1)	0.99974540		9380		46092		554 B	incoming	443->63061(ACK) Win=646
2.5.2022 09:21:05		0.99974540		9380	141.100.20.26	48082	UCP	554 B	Incoming	443-×63061[ACK] Win=646
2.5.2022 09.21.05	Zoom	0.99986530		9383	141.100.20.26	48082	UCP		Incuming	443-+63061(ACK Win=646
									Rows per page:	
Packet Details		Class Activation Map 🎱 Culor Mode 1 🗸 🤇			3	Plain Text Representation		Hex Representation		
<-> Ethernet Header, 14 bytes			~ —				••P•C•••••E		C8F758AD4395881C7F818982880845	
Source Mac. 00:1c 7/:81:09:02							••;••@•?•g••d••		000238978140003F1167CC8D64141A	
Destination Mac: e8:17:50:ed:43:95							•d••••\$••'••••		806488828802244462279618166198	
Ç-9 EPod Hander; 20 bytes Source (p. 141.100.20.26 Destinution (p. 141.100.11.130 Checksam: 6700 Teal Langetts: 277			^				•••••L5_•I••		F8981A189C014C535FD04	986898999
			CAN UN Her 17	CAN WERE REPORTED TO	AM Value AM (referrer / 100 M. prostate)		•••• ••b7•••D	W•	00002077C05986237DCA	3CD445601
				Hire 12			•••••P••5•		0088818EDE08841250008	35821007
							•{P•p•••••		7C877B56C07088601C0017	7E2F48582
Protocol: UCP						••A38•••••(+1+C		BFA5414A400896A7CB052B1A6CC043		
Time to live: 68							625•u•U••K•~+	*	28473235DF75C75587E84	3167E286D
(-) User Datagra	m Protocol (UDP) Header, 8 bj	ytes	~				••h]•••••{u•		E3EE68SDC8FA968ED48E7	375AE7490

Findings:

- The model can be simplified without significant performance loss
 - Since the end of the packet is usually encrypted
- Misleading features
 - Sequence number

In	nut Sizo	Accuracy						
111	Input Size	ISCX2016	IVA2022	VNAT2023				
	130	0.9726	0.9872	0.9985				
	150	0.9800	0.9853	0.9969				
	170	0.9758	0.9887	0.9989				
	200	0.9655	0.9836	0.9976				
	1500	0.9586	0.9781	0.9975				





e: 0.02 (relative) / -516.99 (abs

 Position of each unit of information remains constant, lies in its ability to aggregate local explanations for features across all sample





Towards the Visualization of Aggregated Class Activation Maps to Analyse the Global Contribution of Class Features

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Planned: CGF Submission 2025





Enhancement with domain knowledge

Present work:

- Data Drift
 - maintain model accuracy over time
- Evaluation in the domain is challenging due to limited background in simplified ML concepts
 - Challenges in labeling
 - Data drift is difficult for domain experts to understand and interpret
 - Increased complexity when all components (labeling, drift, XAI) are combined

Enhancement with domain knowledge



Enhancement with domain knowledge

Future work:

- Model Improvement
 - Applying active learning to iteratively improve the model with informative samples
 - Creation of a more robust model
 - For that we need also a solid dataset as well
- Automatic Rule Extraction/Creation using XAI and raw data
- Providing guidance to help experts overcome the complexity

Thank you for your attention!